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(54) **CORRECTING N-GRAM PROBABILITIES BY PAGE VIEW INFORMATION**

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G06F 17/20	(2006.01)
G06F 17/21	(2006.01)

(52) **U.S. Cl.**

CPC ***G06F 17/27*** (2013.01)

(58) **Field of Classification Search**

CPC G06F 17/02
USPC 704/1, 9, 10, 257, 270–275
See application file for complete search history.

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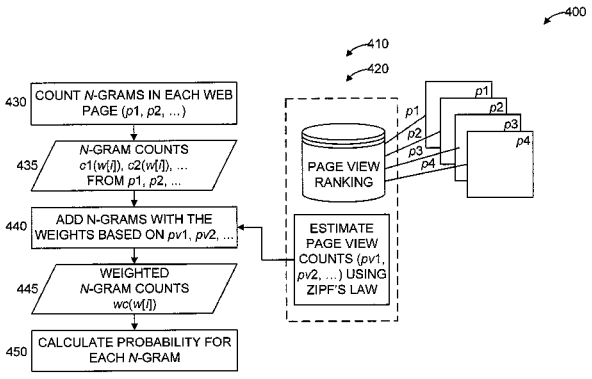
(57) **ABSTRACT**

Methods and a system for calculating N-gram probabilities in a language model. A method includes counting N-grams in each page of a plurality of pages or in each document of a plurality of documents to obtain respective N-gram counts therefor. The method further includes applying weights to the respective N-gram counts based on at least one of view counts and rankings to obtain weighted respective N-gram counts. The view counts and the rankings are determined with respect to the plurality of pages or the plurality of documents. The method also includes merging the weighted respective N-gram counts to obtain merged weighted respective N-gram counts for the plurality of pages or the plurality of documents. The method additionally includes calculating a respective probability for each of the N-grams based on the merged weighted respective N-gram counts.

10 Claims, 7 Drawing Sheets



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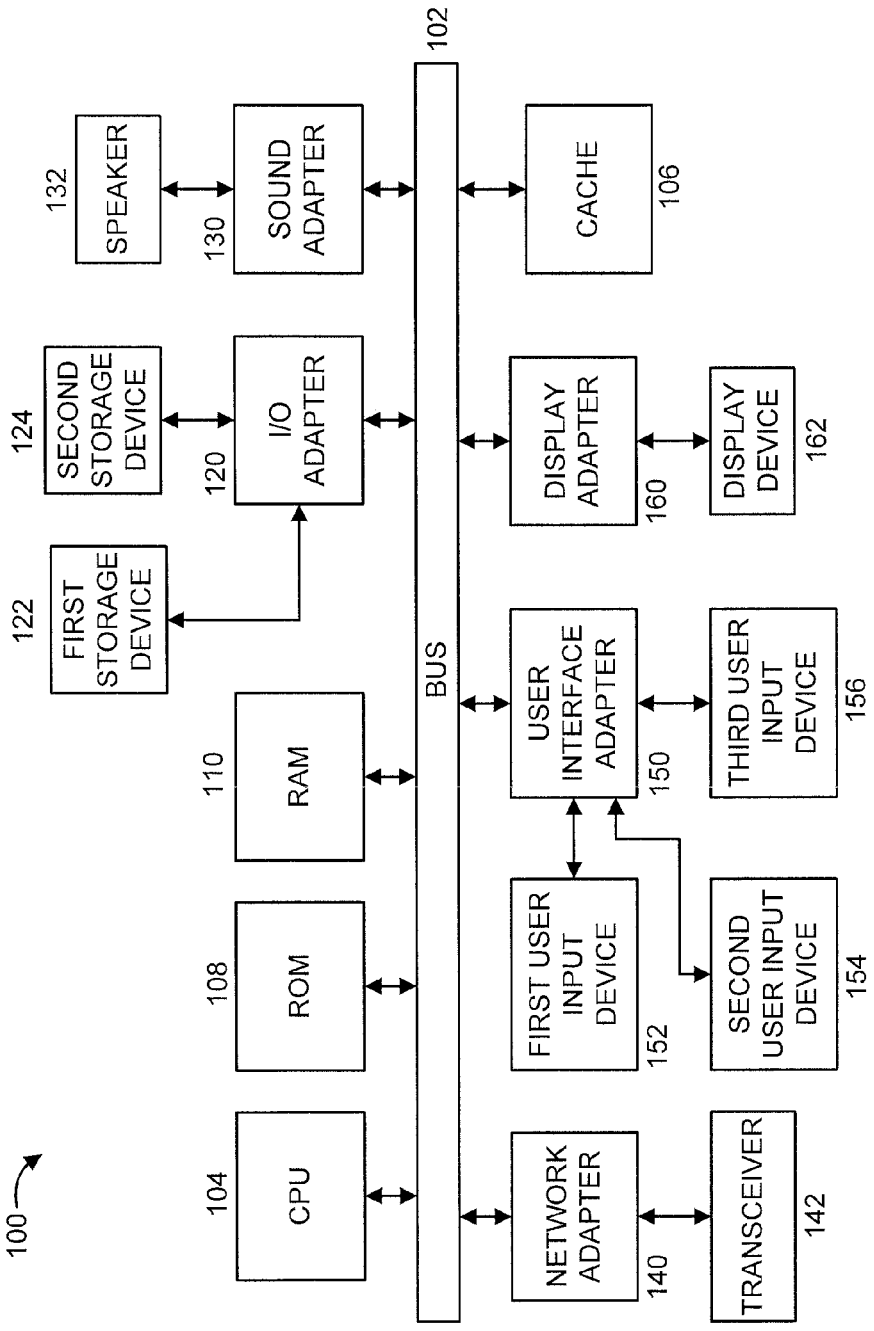
100
CPU
104
ROM
108
RAM
110
FIRST STORAGE DEVICE
122
SECOND STORAGE DEVICE
124
I/O ADAPTER
120
SPEAKER
132
SOUND ADAPTER
130
BUS
102
CACHE
106
DISPLAY ADAPTER
160
DISPLAY DEVICE
162
USER INTERFACE ADAPTER
150
THIRD USER INPUT DEVICE
156
FIRST USER INPUT DEVICE
152
SECOND USER INPUT DEVICE
154
NETWORK ADAPTER
140
TRANSCEIVER
142

FIG. 1

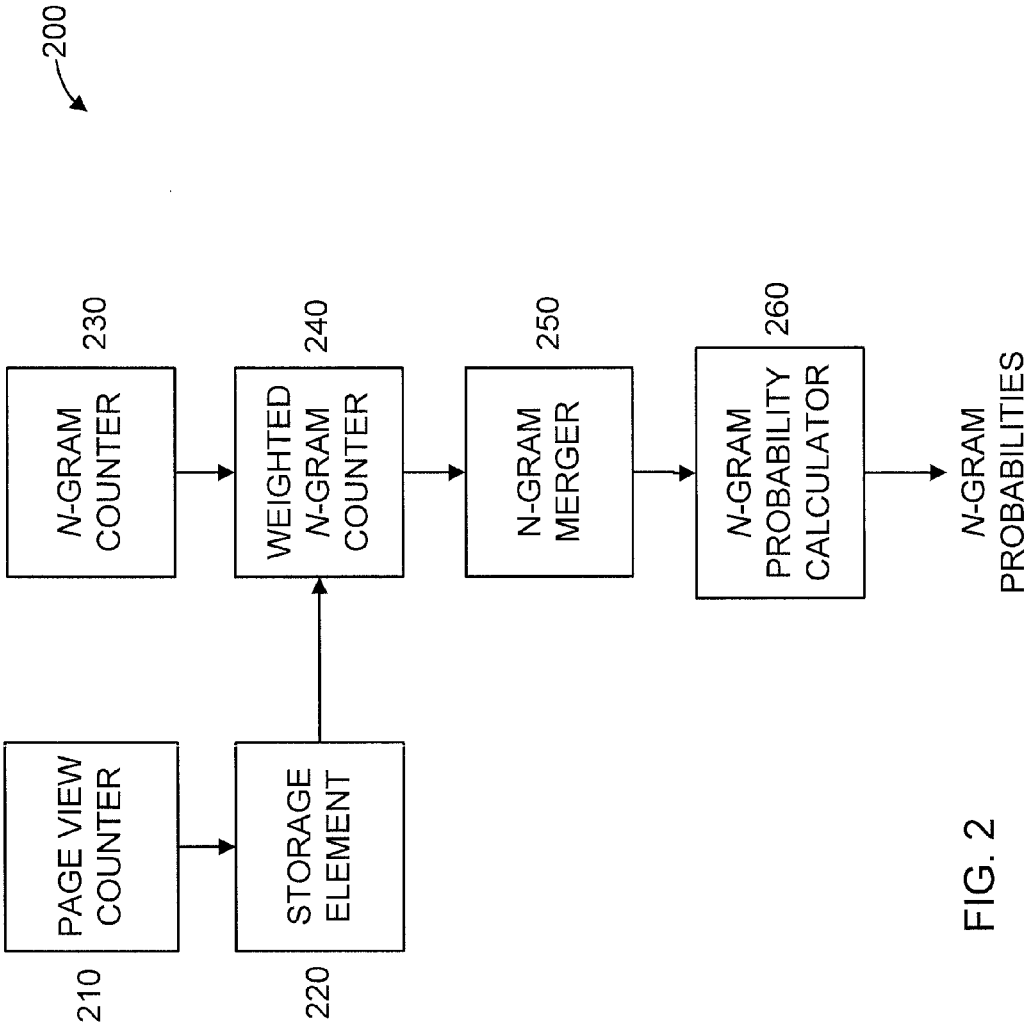
200
230
N-GRAM COUNTER
240
WEIGHTED N-GRAM COUNTER
250
N-GRAM MERGER
260
N-GRAM PROBABILITY CALCULATOR
N-GRAM PROBABILITIES
PAGE VIEW COUNTER
210
STORAGE ELEMENT
220

FIG. 2

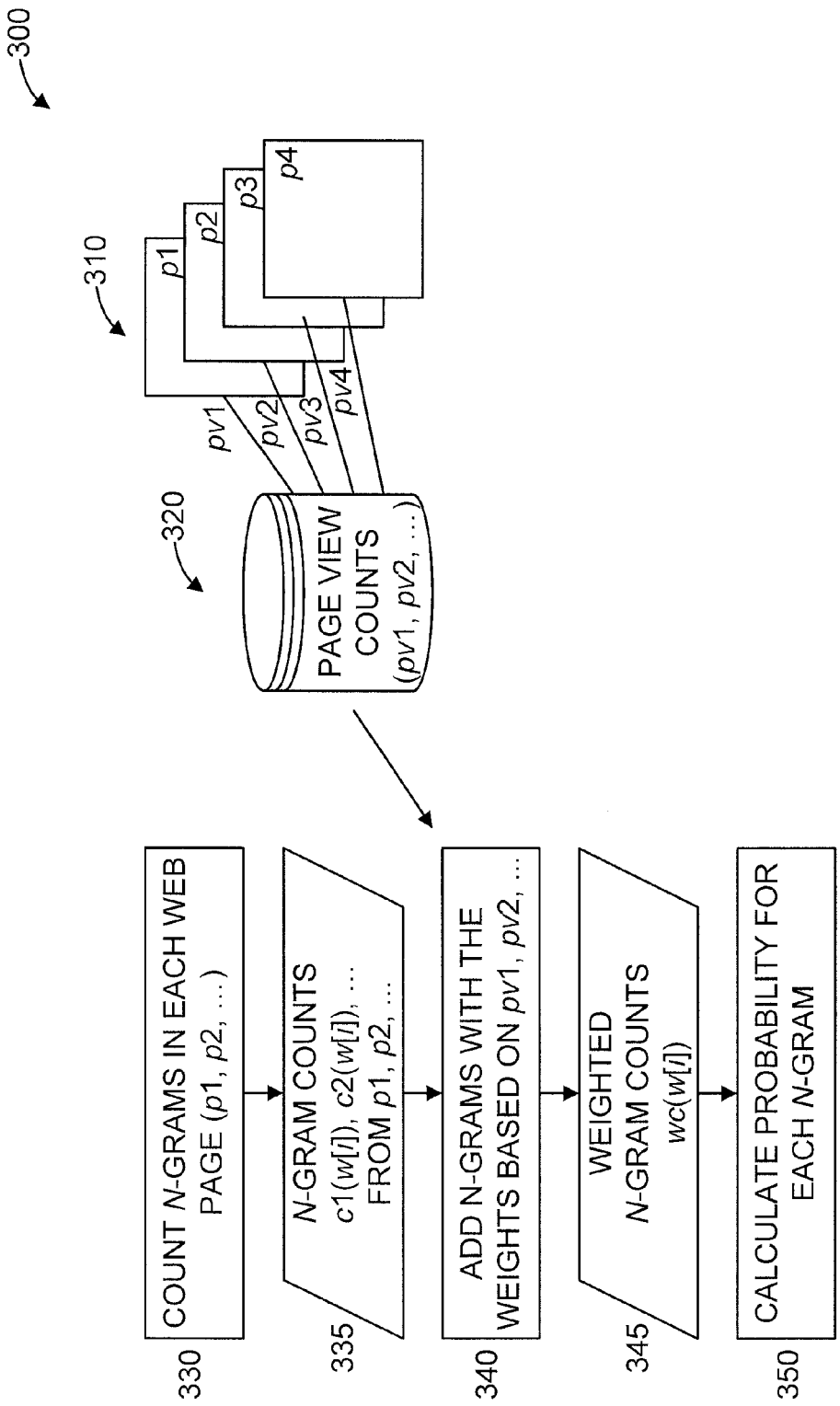
300
310
p1
p2
p3
p4
pv1
pv2
pv3
pv4
320
PAGE VIEW COUNTS (pv1, pv2, ...)
330
COUNT N-GRAMS IN EACH WEB PAGE (p1, p2, ...)
335
N-GRAM COUNTS c1(w[i]), c2(w[i]), ... FROM p1, p2, ...
340
ADD N-GRAMS WITH THE WEIGHTS BASED ON pv1, pv2, ...
345
WEIGHTED N-GRAM COUNTS wc(w[i])
350
CALCULATE PROBABILITY FOR EACH N-GRAM

FIG. 3

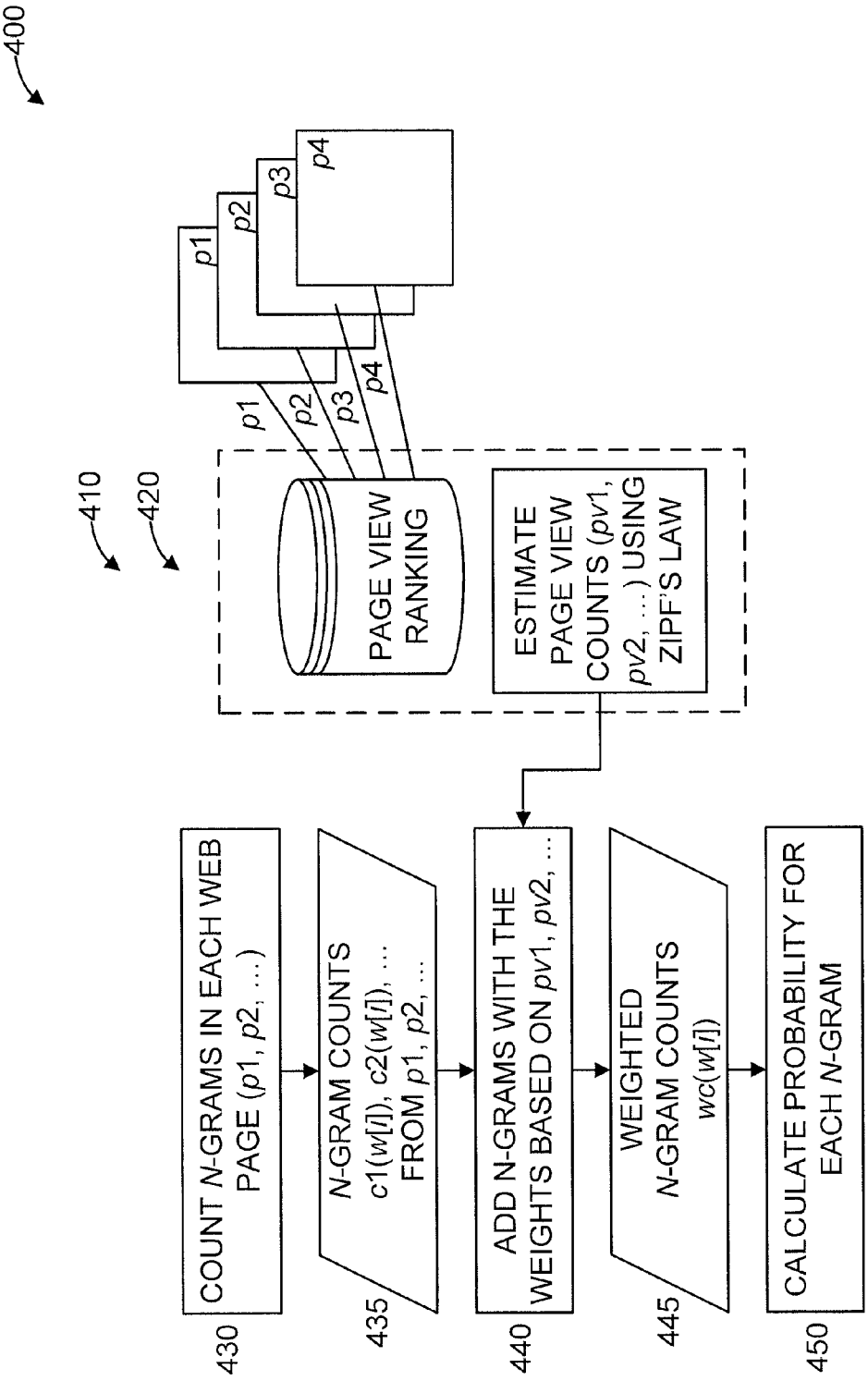
400
410
420
p1
p2
p3
p4
PAGE VIEW RANKING
ESTIMATE PAGE VIEW COUNTS (pv1, pv2, ...) USING ZIPF'S LAW
COUNT N-GRAMS IN EACH WEB PAGE (p1, p2, ...)
N-GRAM COUNTS c1(w[i]), c2(w[i]), ... FROM p1, p2, ...
ADD N-GRAMS WITH THE WEIGHTS BASED ON pv1, pv2, ...
WEIGHTED N-GRAM COUNTS wc(w[i])
CALCULATE PROBABILITY FOR EACH N-GRAM
430
435
440
445
450

FIG. 4

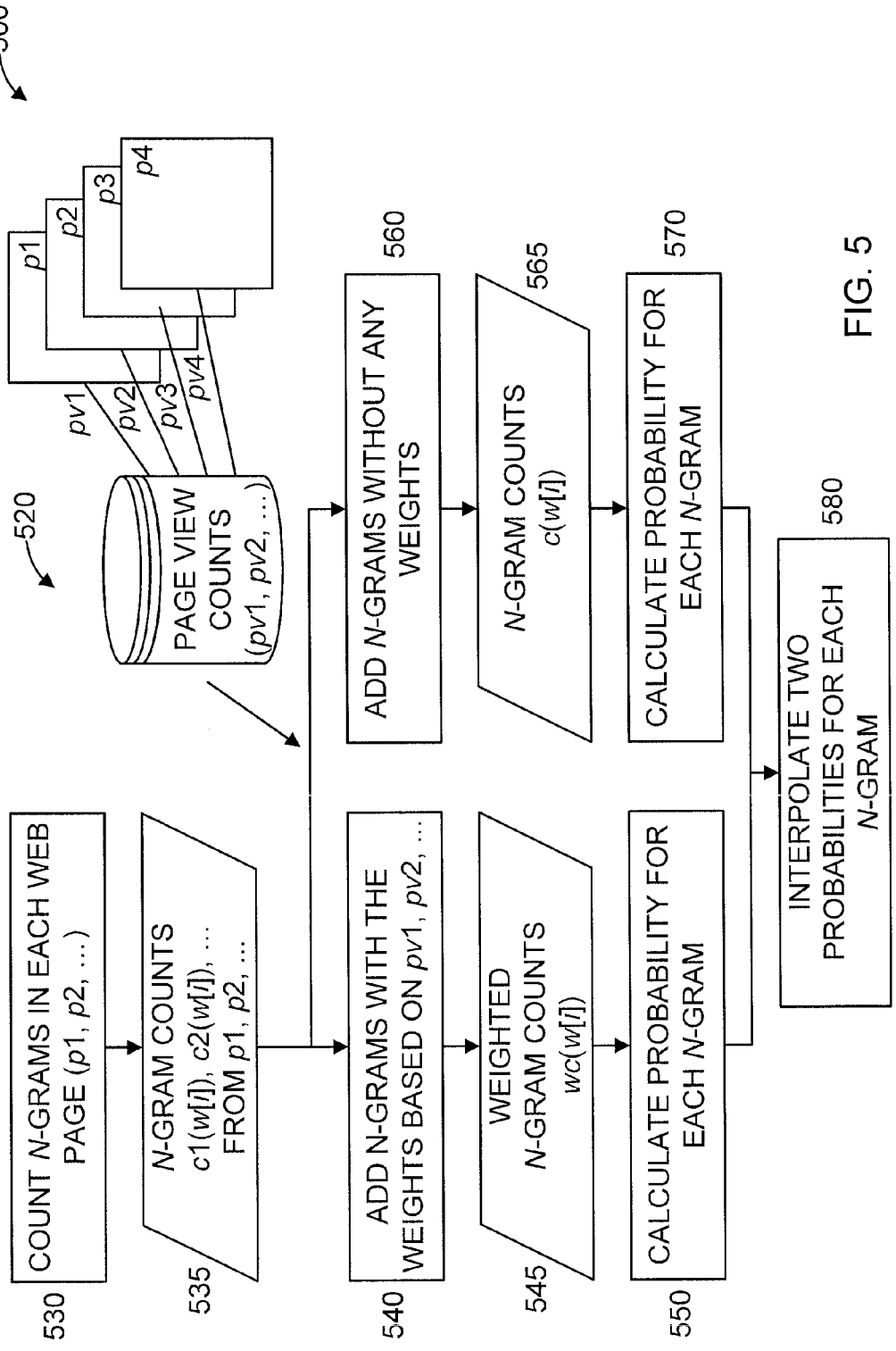
500
510
p1
p2
p3
p4
pv1
pv2
pv3
pv4
520
PAGE VIEW COUNTS (pv1, pv2, ...)
COUNT N-GRAMS IN EACH WEB PAGE (p1, p2, ...)
530
N-GRAM COUNTS c1(w[i]), c2(w[i]), ... FROM p1, p2, ...
535
ADD N-GRAMS WITH THE WEIGHTS BASED ON pv1, pv2, ...
540
WEIGHTED N-GRAM COUNTS wc(w[i])
545
CALCULATE PROBABILITY FOR EACH N-GRAM
550
ADD N-GRAMS WITHOUT ANY WEIGHTS
560
N-GRAM COUNTS c(w[i])
565
CALCULATE PROBABILITY FOR EACH N-GRAM
570
INTERPOLATE TWO PROBABILITIES FOR EACH N-GRAM
580

FIG. 5

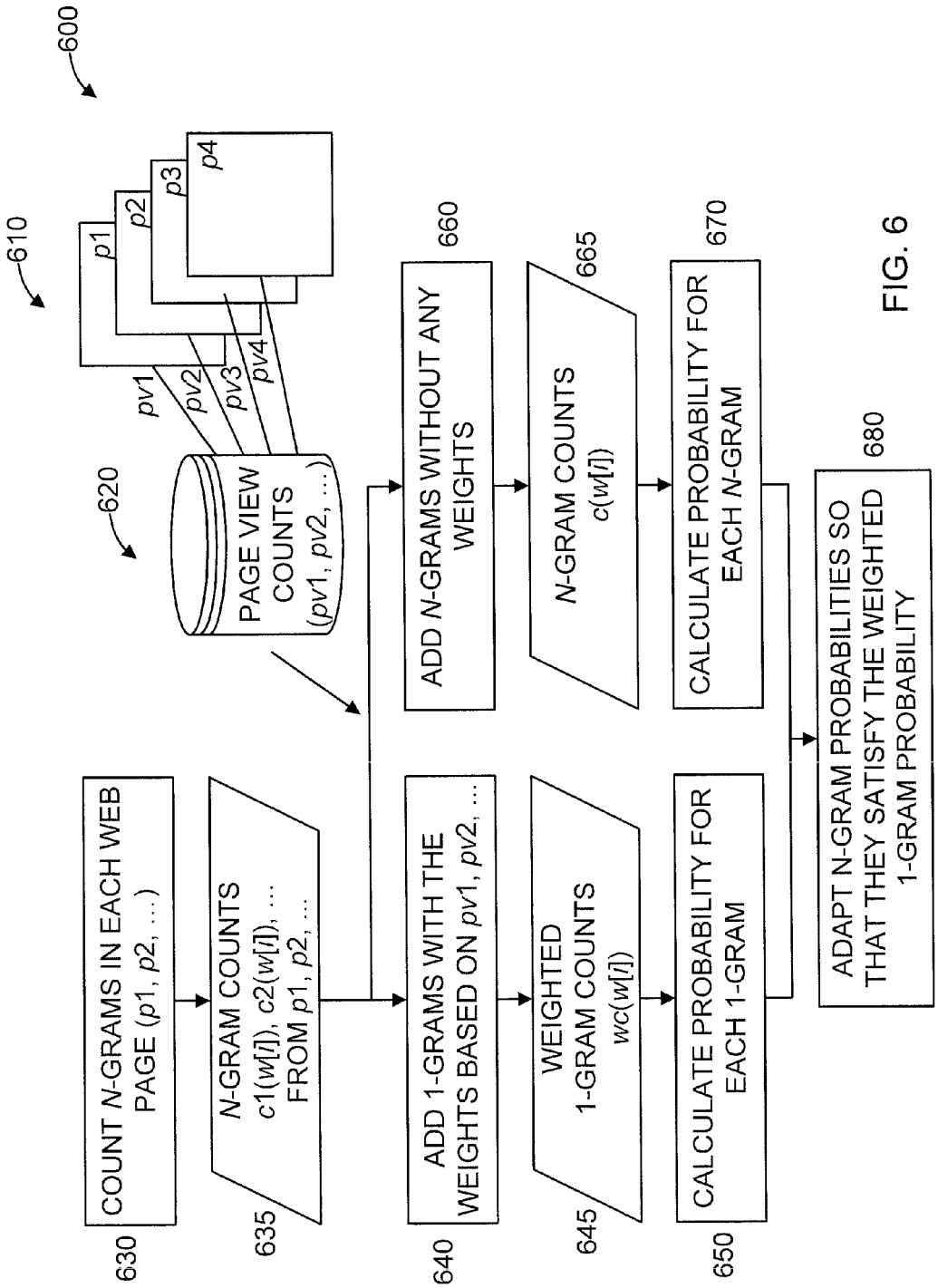
600
610
p1
p2
p3
p4
pv1
pv2
pv3
pv4
620
PAGE VIEW COUNTS (pv1, pv2, ...)
COUNT N-GRAMS IN EACH WEB PAGE (p1, p2, ...)
630
N-GRAM COUNTS c1(w[i]), c2(w[i]), ... FROM p1, p2, ...
635
ADD 1-GRAMS WITH THE WEIGHTS BASED ON pv1, pv2, ...
640
WEIGHTED 1-GRAM COUNTS wc(w[i])
645
CALCULATE PROBABILITY FOR EACH 1-GRAM
650
ADD N-GRAMS WITHOUT ANY WEIGHTS
660
N-GRAM COUNTS c(w[i])
665
CALCULATE PROBABILITY FOR EACH N-GRAM
670
ADAPT N-GRAM PROBABILITIES SO THAT THEY SATISFY THE WEIGHTED 1-GRAM PROBABILITY
680

FIG. 6

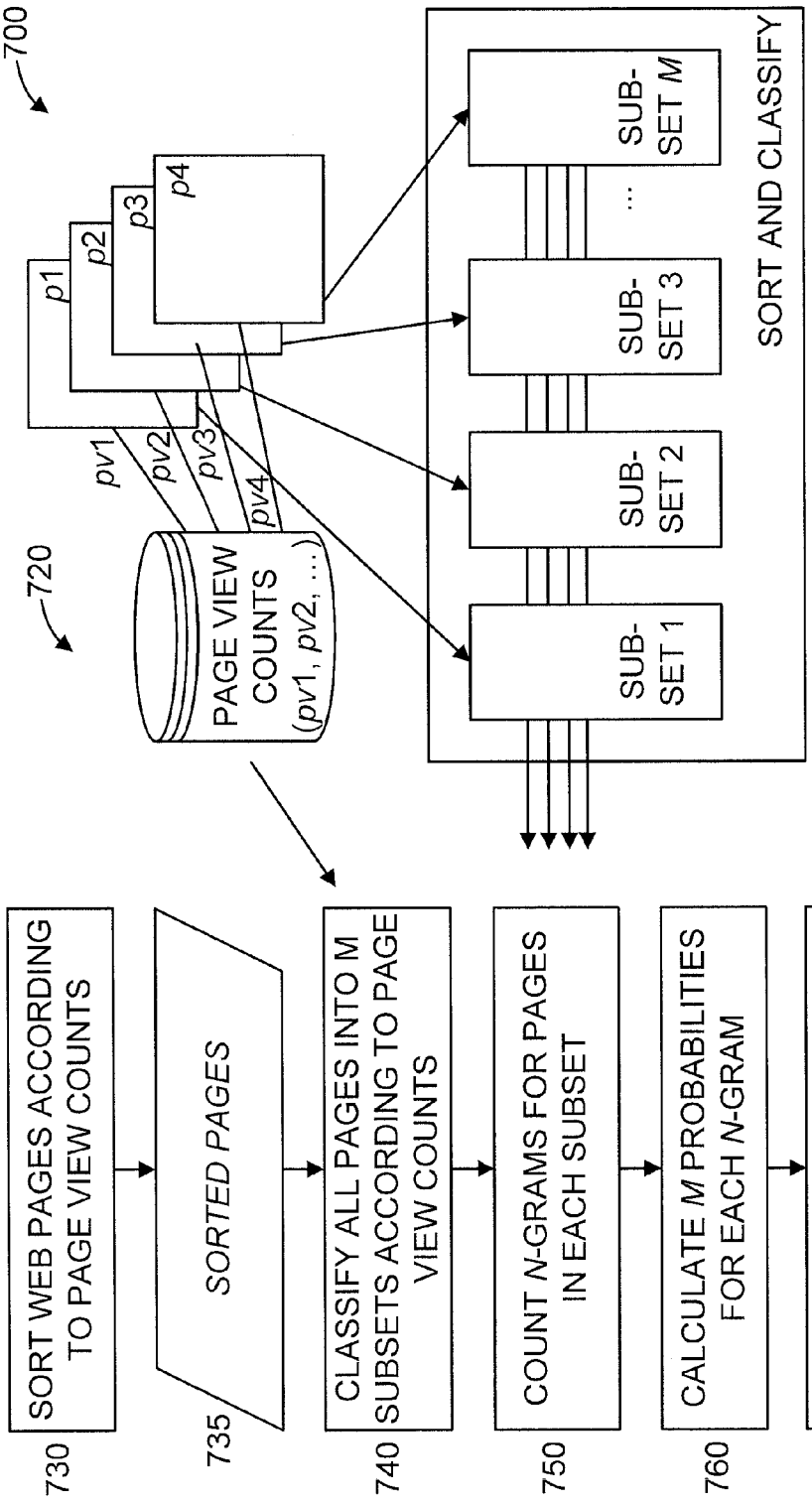
700
710
p1
p2
p3
p4
pv1
pv2
pv3
pv4
720
PAGE VIEW COUNTS (pv1, pv2, ...)
SUB-SET 1
SUB-SET 2
SUB-SET 3
...
SUB-SET M
SORT AND CLASSIFY
730
SORT WEB PAGES ACCORDING TO PAGE VIEW COUNTS
735
SORTED PAGES
740
CLASSIFY ALL PAGES INTO M SUBSETS ACCORDING TO PAGE VIEW COUNTS
750
COUNT N-GRAMS FOR PAGES IN EACH SUBSET
760
CALCULATE M PROBABILITIES FOR EACH N-GRAM
770
INTERPOLATE M PROBABILITIES FOR EACH N-GRAM

FIG. 7

CORRECTING N-GRAM PROBABILITIES BY PAGE VIEW INFORMATION

BACKGROUND

1. Technical Field

The present invention relates generally to language models and, in particular, to correcting N-gram probabilities by page view information.

2. Description of the Related Art

An N-gram based language model is a construct/method for predicting probabilities of sentences on the basis of occurrence probabilities of N word sequences, and widely used in speech recognition, machine translation, and information retrieval. Since a large amount of training data is required to estimate probabilities accurately, it is usual to crawl web sites and collect the training data. N-gram probability is calculated from the frequency of each event. The sizes of texts on topics will be sharply reflected in N-gram probabilities on the corresponding topics.

Typically, the number of web sites and the total size of documents related to a topic are considered to be correlated with the frequency of the topic mentioned in Internet users. However, the preceding statement is not always true. For example, sometimes a very small number of eager contributors write many articles on a topic. Taking WIKIPEDIA® as an example, the sizes of the documents on specific topics (i.e., train, game) or person (entertainers) are significantly larger than others. However the topics are not necessarily mentioned with high frequencies.

In "suggest functions" provided in search engines (e.g., GOOGLE®), candidate words and phrases will be suggested on the basis of the frequencies of users' inputs. The probabilities should be almost optimal. However, such frequencies are not available to entities other than the search engine providers.

SUMMARY

According to an aspect of the present invention, a method is provided for calculating N-gram probabilities in a language model. The method includes counting N-grams in each page of a plurality of pages or in each document of a plurality of documents to obtain respective N-gram counts therefor. The method further includes applying weights to the respective N-gram counts based on at least one of view counts and rankings to obtain weighted respective N-gram counts. The view counts and the rankings are determined with respect to the plurality of pages or the plurality of documents. The method also includes merging the weighted respective N-gram counts to obtain merged weighted respective N-gram counts for the plurality of pages or the plurality of documents. The method additionally includes calculating a respective probability for each of the N-grams based on the merged weighted respective N-gram counts.

According to another aspect of the present invention, a method is provided for calculating N-gram probabilities in a language model. The method includes sorting a plurality of pages or a plurality of documents based on at least one of view counts and rankings to obtain sorted pages or sorted documents. The method further includes classifying the sorted pages or the sorted documents into M subsets. The method also includes counting N-grams in each of the M-subsets. The method additionally includes estimating respective N-gram probabilities for each of the N-grams in each of the M-subsets using a maximum likelihood method. The method further includes interpolating the estimated respective N-gram probabilities to minimize a cross entropy there between.

According to yet another aspect of the present invention, a system is provided for calculating N-gram probabilities in a language model. The system includes an N-gram counter for counting N-grams in each page of a plurality of pages or in each document of a plurality of documents to obtain respective N-gram counts therefor. The system further includes a weighted N-gram counter for applying weights to the respective N-gram counts based on at least one of view counts and rankings to obtain weighted respective N-gram counts. The view counts and the rankings are determined with respect to the plurality of pages or the plurality of documents. The system also includes an N-gram merger for merging the weighted respective N-gram counts to obtain merged weighted respective N-gram counts for the plurality of pages or the plurality of documents. The system additionally includes a probability calculator for calculating a respective probability for each of the N-grams based on the merged weighted respective N-gram counts.

These and other features and advantages will become apparent from the following detailed description of illustrative embodiments thereof, which is to be read in connection with the accompanying drawings.

BRIEF DESCRIPTION OF DRAWINGS

The disclosure will provide details in the following description of preferred embodiments with reference to the following figures wherein:

FIG. **1** shows an exemplary processing system **100** to which the present invention may be applied, according to an embodiment of the present invention;

FIG. **2** shows a system **200** for correcting N-frame probabilities by page view information, in accordance with an embodiment of the present principles;

FIG. **3** shows a method for correcting N-gram probabilities by page view information, in accordance with an embodiment of the present principles;

FIG. **4** shows a method for correcting N-gram probabilities by page view information, in accordance with a first alternate embodiment of the present principles;

FIG. **5** shows a method for correcting N-gram probabilities by page view information, in accordance with a second alternate embodiment of the present principles;

FIG. **6** shows a method for correcting N-gram probabilities by page view information, in accordance with a third alternate embodiment of the present principles; and

FIG. **7** shows a method for correcting N-gram probabilities by page view information, in accordance with a fourth alternate embodiment of the present principles.

DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS

The present principles are directed to correcting N-gram probabilities by page view information. While one or more embodiments of the present principles are described herein with respect to speech recognition, it is to be appreciated that the present principles are not limited to the same, and can be used with respect to other technological areas and applications, while maintaining the spirit of the present principles. For example, the present principles can also be implemented with respect to machine translation, part-of-speech tagging, parsing, and information retrieval. These and other applications to which the present principles can be applied are readily

determined by one of ordinary skill in the art, while maintaining the spirit of the present principles.

FIG. **1** shows an exemplary processing system **100** to which the present principles may be applied, in accordance with an embodiment of the present principles. The processing system **100** includes at least one processor (CPU) **104** operatively coupled to other components via a system bus **102**. A cache **106**, a Read Only Memory (ROM) **108**, a Random Access Memory (RAM) **110**, an input/output (I/O) adapter **120**, a sound adapter **130**, a network adapter **140**, a user interface adapter **150**, and a display adapter **160**, are operatively coupled to the system bus **102**.

A first storage device **122** and a second storage device **124** are operatively coupled to system bus **102** by the I/O adapter **120**. The storage devices **122** and **124** can be any of a disk storage device (e.g., a magnetic or optical disk storage device), a solid state magnetic device, and so forth. The storage devices **122** and **124** can be the same type of storage device or different types of storage devices.

A speaker **132** is operative coupled to system bus **102** by the sound adapter **130**.

A transceiver **142** is operatively coupled to system bus **102** by network adapter **140**.

A first user input device **152**, a second user input device **154**, and a third user input device **156** are operatively coupled to system bus **102** by user interface adapter **150**. The user input devices **152**, **154**, and **156** can be any of a keyboard, a mouse, a keypad, an image capture device, a motion sensing device, a microphone, a device incorporating the functionality of at least two of the preceding devices, and so forth. Of course, other types of input devices can also be used, while maintaining the spirit of the present principles. The user input devices **152**, **154**, and **156** can be the same type of user input device or different types of user input devices. The user input devices **152**, **154**, and **156** are used to input and output information to and from system **100**.

A display device **162** is operatively coupled to system bus **102** by display adapter **160**.

Of course, the processing system **100** may also include other elements (not shown), as readily contemplated by one of skill in the art, as well as omit certain elements. For example, various other input devices and/or output devices can be included in processing system **100**, depending upon the particular implementation of the same, as readily understood by one of ordinary skill in the art. For example, various types of wireless and/or wired input and/or output devices can be used. Moreover, additional processors, controllers, memories, and so forth, in various configurations can also be utilized as readily appreciated by one of ordinary skill in the art. These and other variations of the processing system **100** are readily contemplated by one of ordinary skill in the art given the teachings of the present principles provided herein.

Moreover, it is to be appreciated that system **200** described below with respect to FIG. **2** is a system for implementing respective embodiments of the present principles. Part or all of processing system **100** may be implemented in one or more of the elements of system **200**.

Further, it is to be appreciated that processing system **100** may perform at least part of the method described herein including, for example, at least part of method **300** of FIG. **3** and/or at least part of method **400** of FIG. **4** and/or at least part of method **500** of FIG. **5** and/or at least part of method **600** of FIG. **6** and/or at least part of method **700** of FIG. **7**. Similarly, part or all of system **200** may be used to perform at least part of method **300** of FIG. **3** and/or at least part of method **400** of FIG. **4** and/or at least part of method **500** of FIG. **5** and/or at least part of method **600** of FIG. **6** and/or at least part of method **700** of FIG. **7**.

FIG. **2** shows a system **200** for correcting N-frame probabilities by page view information, in accordance with an embodiment of the present principles. The system includes a page view counter **210**, a storage element **220**, a N-gram counter **230**, a weighted N-gram counter **240**, and a N-gram probability calculator **250**. The page view counter **210** determines/estimates page view counts from web pages. The storage element **220** stores at least the page view counts. The N-gram counter **230** generates N-gram counts from the web pages. The weighted N-gram counter **240** generates weighted N-gram counts. The N-gram probability calculator **250** calculates N-gram probabilities. The functions of the elements of system **200** are described in further detail with respect to the following flowcharts.

FIG. **3** shows a method for correcting N-gram probabilities by page view information, in accordance with an embodiment of the present principles.

At step **310**, determine page view counts (pv1, pv2, . . .) from web pages (p1, p2, . . .).

At step **320**, store the page view counts (pv1, pv2, . . .) in a storage element (e.g., a database).

At step **330**, count N-grams in each web page (p1, p2, . . .). Further regarding step **330**, an output thereof (denoted by the reference numeral **335**) includes the N-gram counts c1(w[i]), c2(w[i]), . . . from p1, p2, ...

At step **340**, add the N-grams with the weights based on pv1, pv2, ... Further regarding step **340**, an output thereof (denoted by the reference numeral **345**) includes the weighted N-gram counts wc(w[i]).

At step **350**, calculate the probability for each N-gram.

As will be appreciated by one skilled in the art, aspects of the present invention may be embodied as a system, method or computer program product. Accordingly, aspects of the present invention may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "circuit," "module" or "system." Furthermore, aspects of the present invention may take the form of a computer program product embodied in one or more computer readable medium(s) having computer readable program code embodied thereon.

Any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium. A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any suitable combination of the foregoing. More specific examples (a non-exhaustive list) of the computer readable storage medium would include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain, or store a program for use by or in connection with an instruction execution system, apparatus, or device.

A computer readable signal medium may include a propagated data signal with computer readable program code

embodied therein, for example, in baseband or as part of a carrier wave. Such a propagated signal may take any of a variety of forms, including, but not limited to, electro-magnetic, optical, or any suitable combination thereof. A computer readable signal medium may be any computer readable medium that is not a computer readable storage medium and that can communicate, propagate, or transport a program for use by or in connection with an instruction execution system, apparatus, or device.

Program code embodied on a computer readable medium may be transmitted using any appropriate medium, including but not limited to wireless, wireline, optical fiber cable, RF, etc., or any suitable combination of the foregoing.

Computer program code for carrying out operations for aspects of the present invention may be written in any combination of one or more programming languages, including an object oriented programming language such as Java, Smalltalk, C++ or the like and conventional procedural programming languages, such as the "C" programming language or similar programming languages. The program code may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection may be made to an external computer (for example, through the Internet using an Internet Service Provider).

Aspects of the present invention are described below with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems) and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

These computer program instructions may also be stored in a computer readable medium that can direct a computer, other programmable data processing apparatus, or other devices to function in a particular manner, such that the instructions stored in the computer readable medium produce an article of manufacture including instructions which implement the function/act specified in the flowchart and/or block diagram block or blocks.

The computer program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other devices to cause a series of operational steps to be performed on the computer, other programmable apparatus or other devices to produce a computer implemented process such that the instructions which execute on the computer or other programmable apparatus provide processes for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

The flowchart and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods and computer program products according to various embodiments of the present invention. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function(s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

Reference in the specification to "one embodiment" or "an embodiment" of the present principles, as well as other variations thereof, means that a particular feature, structure, characteristic, and so forth described in connection with the embodiment is included in at least one embodiment of the present principles. Thus, the appearances of the phrase "in one embodiment" or "in an embodiment", as well any other variations, appearing in various places throughout the specification are not necessarily all referring to the same embodiment.

It is to be appreciated that the use of any of the following "/", "and/or", and "at least one of", for example, in the cases of "A/B", "A and/or B" and "at least one of A and B", is intended to encompass the selection of the first listed option (A) only, or the selection of the second listed option (B) only, or the selection of both options (A and B). As a further example, in the cases of "A, B, and/or C" and "at least one of A, B, and C", such phrasing is intended to encompass the selection of the first listed option (A) only, or the selection of the second listed option (B) only, or the selection of the third listed option (C) only, or the selection of the first and the second listed options (A and B) only, or the selection of the first and third listed options (A and C) only, or the selection of the second and third listed options (B and C) only, or the selection of all three options (A and B and C). This may be extended, as readily apparent by one of ordinary skill in this and related arts, for as many items listed.

A description will now be given of the use of page views, in accordance with an embodiment of the present principles.

In various web sites such as WIKIPEDIA®, statistics on how many people visited documents (pages), which is called page-view count, is available. Moreover, some statistics are not frequency of visiting, but simply ranking. For the purposes of the present principles, we interchangeably call viewing frequencies (e.g., with respect to a particular page, document, etc.) as "page-view count" and "view count". Moreover, while some embodiments specifically mention page-view counts, it is to be appreciated rankings can also be used in place of, or in addition to, the page-view counts.

In accordance with the present principles, we propose a method for correcting N-gram probabilities using page-view counts, and for creating a language model that is dependent not on contributors but on topics mentioned by general Internet users. It is to be appreciated that page-view count does not correspond to the frequency of each word or phrase and is not applicable to N-gram probability estimations straightforwardly. We therefore calculate N-gram probabilities considering page-view count as follows.

According to a first embodiment, we count N-grams in each page (or document), and merge the counts putting page-view based weights on them. Let an N word sequence (N-gram) be $w_i=w_{i-N-1}\ w_{i-N-2}, \ldots, w_i$ and the page-view of a

page (or document) be $PageView_j$, where w_i indicates the i^{th} word in the N word sequence. Weighted counts $Count_{pv}(w_i)$ and N-gram probability $P_{pv}(w_i)$ are calculated as follows:

$$Count_{pv}(w_i) = \frac{\sum_j PageView_j \times Count_j(w_i)}{\sum_i PageView_j}, \quad (1)$$

$$P_{pv}(w_i) = \frac{Count_{pv}(w_i)}{\sum_i Count_{pv}(w_i)}$$

The above method is the most straight-forward one, applying page view counts to a language model. If reliable page counts are available, then the estimated probabilities will be good enough. However the following challenges are sometimes encountered.

Regarding a first challenge, page view counts are unknown, but page view ranking based on the counts is available. Actually in many blog sites, page rankings are open to the public. On the other hand, the availability of page view counts is limited.

Regarding a second challenge, page view counts are available, but they are not reliable enough. For example, the page view counts in the short term (e.g., one day) are usually unreliable.

Regarding a third challenge, specific pages on a popular name or event are accessed a large number of times. The above method can fail due to over training. Obtained parameter values are not reliable.

Regarding a fourth challenge, weighting based on page view counts sometimes results in drawbacks due to the use of function words which are not topic-dependent. In particular, it is often the case that function words are usually omitted when provided as inputs to a search engine.

A description will now be given of some variations of the present principles.

In a first alternate embodiment directed to the first challenge described herein before, the following applies. Even if just ranking is available, it is known that page-view follows the Zipf's Law, so we can use estimated frequencies instead of the frequencies themselves. The first alternate embodiment is shown and described with respect to FIG. **4**.

FIG. **4** shows a method for correcting N-gram probabilities by page view information, in accordance with a first alternate embodiment of the present principles.

At step **410**, estimate page view counts (pv1, pv2, . . .) from page view rankings using Zipf's Law.

At step **420**, store the estimated page view counts (pv1, pv2, . . .) in a storage element (e.g., a database).

At step **430**, count N-grams in each web page (p1, p2, . . .). Further regarding step **430**, an output thereof (denoted by the reference numeral **435**) includes the N-gram counts c1(w[i]), c2(w[i]), . . . from p1, p2, ...

At step **440**, add the N-grams with the weights based on pv1, pv2, ... Further regarding step **440**, an output thereof (denoted by the reference numeral **445**) includes the weighted N-gram counts wc(w[i]).

At step **450**, calculate the probability for each N-gram.

In a second alternate embodiment directed to the second and third challenges described herein before, the following applies. Weights are calculated not by the actual page view counts, but by the logarithm of the actual page view counts. In some cases quantization (0, 1, and others) of the actual page view counts or logs thereof could be helpful. Moreover, we estimate N-gram probability in the following two ways: (1) maximum-likelihood ($P_{ml}(w_i)$), no-weighted); and (2) Equation (1) (P_{pv}, (w_i), weighted), and interpolate them with λ, where λ is an interpolation coefficient that is chosen with the lowest cross entropy (perplexity), for example, for real transcribed text. Note that this data is called a "development set" and is small enough. $P(w_i)$ is calculated as follows:

$$P(w_i)=\lambda P_{ml}(w_i)+(1+\lambda)P_{pv}(w_i) \quad (2).$$

The second alternate embodiment is shown and described with respect to FIG. **5**.

FIG. **5** shows a method for correcting N-gram probabilities by page view information, in accordance with a second alternate embodiment of the present principles.

At step **510**, determine page view counts (pv1, pv2, . . .) from web pages (p1, p2, . . .).

At step **520**, store the page view counts (pv1, pv2, . . .) in a storage element (e.g., a database).

At step **530**, count N-grams in each web page (p1, p2, . . .). Further regarding step **530**, an output thereof (denoted by the reference numeral **535**) includes the N-gram counts c1(w[i]), c2(w[i]), . . . from p1, p2, ... The output **535** is provided to both steps **540** and **560**.

At step **540**, add the N-grams with the weights based on pv1, pv2, ... Further regarding step **540**, an output thereof (denoted by the reference numeral **545**) includes the weighted N-gram counts wc(w[i]).

At step **550**, calculate the probability for each N-gram.

At step **560**, add the N-grams without any weights. Further regarding step **560**, an output thereof (denoted by the reference numeral **565**) includes the N-gram counts c(w[i]).

At step **570**, calculate the probability for each N-gram.

At step **580**, interpolate two probabilities for each N-gram, e.g., based on the probabilities for each N-gram calculated at steps **550** and **570**.

In a third alternate embodiment directed to the fourth challenge described herein before, the following applies. Many utterances to speech recognizers for search engines are not sentences but word combinations. We can use titles and section headers with page-views for creating a better language model, where low-order N-gram probability is calculated in Equation (1), and the all higher N-gram probabilities are adapted to it using log-linear interpolation. For example, adaptation by the following formula is applicable. This is a sample for 3-gram:

$$P_{adopted}(w_i|w_{i-1}w_{i-2}) = \frac{1}{z}\left(\frac{P_{weighted}(w_i)}{P_{unweighted}(w_i)}\right)^{\beta} P_{unweighted}(w_i|w_{i-1}w_{i-2})$$

where $P_{adapted}$, $P_{weighted}$ and $P_{unweighted}$ are adapted, weighted, and unweighted N-gram probabilities, respectively. Z is a constant for normalization. β is a controlling parameter. The third alternate embodiment is shown and described with respect to FIG. **6**.

FIG. **6** shows a method for correcting N-gram probabilities by page view information, in accordance with a third alternate embodiment of the present principles.

At step **610**, determine page view counts (pv1, pv2, . . .) from web pages (p1, p2, . . .).

At step **620**, store the page view counts (pv1, pv2, . . .) in a storage element (e.g., a database).

At step **630**, count N-grams in each web page (p1, p2, . . .). Further regarding step **630**, an output thereof (denoted by the reference numeral **635**) includes the N-gram counts c1(w[i]), c2(w[i]), . . . from p1, p2, ... The N-grams

counts will include 1-gram counts. The output **635** is provided to both steps **640** and **660**.

At step **640**, add the 1-grams with the weights based on pv1, pv2, ... Further regarding step **640**, an output thereof (denoted by the reference numeral **645**) includes the weighted 1-gram counts wc(w[i]).

At step **650**, calculate the probability for each 1-gram.

At step **660**, add the N-grams without any weights. Further regarding step **660**, an output thereof (denoted by the reference numeral **665**) includes the N-gram counts c(w[i]).

At step **670**, calculate the probability for each N-gram.

At step **680**, adapt the N-gram probabilities so that they satisfy the weighted 1-gram probability, e.g., based on the probabilities for each 1-gram and N-gram calculated at steps **650** and **670**, respectively.

In a fourth alternate embodiment directed to the second and third challenges described herein before, the following applies. Sort web pages according to page view counts and classified them into M subsets (S_1, S_2, . . . , S_M). Count N-grams in each subset, and estimate N-gram probabilities $p_k(w_i)$, k=1, . . . , M by a maximum likelihood method. Then interpolate these probabilities so that the perplexity (cross entropy) of the development set should be minimized. Final probabilities Pe(wi) will be obtained. This method is formulated as follows:

$$Pe(w_i)=\Sigma_{K=1}^{M} v_k \times P_k(w_i)$$

where the weights v=(v1, v2, . . . , v_M) are calculated using the following formulae:

$$v=\arg\min_v(-\Sigma_{w_i \epsilon T} v_k p_k(w_i)\log(v_k p_k(w_i)))$$

where $\Sigma_k v_k=1$. The fourth alternate embodiment is shown and described with respect to FIG. **7**.

FIG. **7** shows a method for correcting N-gram probabilities by page view information, in accordance with a fourth alternate embodiment of the present principles.

At step **710**, determine page view counts (pv1, pv2, . . .) from web pages (p1, p2, . . .).

At step **720**, store the page view counts (pv1, pv2, . . .) in a storage element (e.g., a database).

At step **730**, sort the web pages according to page view counts. Further regarding step **730**, an output thereof (denoted by the reference numeral **735**) includes sorted pages.

At step **740**, classify all pages into M subsets according to the page view counts.

At step **750**, count the N-grams for the pages in each of the M subsets to obtain N-gram counts therefor.

At step **760**, calculate M probabilities for each N-gram.

At step **770**, interpolate the M probabilities for each N-gram to obtain interpolated probabilities for each N-gram.

Some of the many benefits of the present principles will now be described. It is expected that we can correct the dependency on text size, which is subject to the numbers of contributors and their eagerness, and create a better language model reflecting on the frequent topics which users really mention. The present principles will make it possible that to perform better modeling for those topics without collecting large amounts of real (field) data, which cannot be collected except by search engine providers.

Having described preferred embodiments of a system and method (which are intended to be illustrative and not limiting), it is noted that modifications and variations can be made by persons skilled in the art in light of the above teachings. It is therefore to be understood that changes may be made in the particular embodiments disclosed which are within the scope of the invention as outlined by the appended claims. Having thus described aspects of the invention, with the details and particularity required by the patent laws, what is claimed and desired protected by Letters Patent is set forth in the appended claims.

What is claimed is:

1. A method for calculating N-gram probabilities in a language model, comprising:

counting N-grams in each page of a plurality of pages or in each document of a plurality of documents to obtain respective N-gram counts therefor;

applying weights to the respective N-gram counts based on at least one of view counts and rankings to obtain weighted respective N-gram counts, the view counts and the rankings determined with respect to the plurality of pages or the plurality of documents;

merging the weighted respective N-gram counts to obtain merged weighted respective N-gram counts for the plurality of pages or the plurality of documents;

calculating a respective probability for each of the N-grams based on the merged weighted respective N-gram counts; and

decoding an utterance, by a speech recognition system, based on the N-gram probabilities in the language model.

2. The method of claim **1**, wherein the view counts are estimated using Zipf's Law.

3. The method of claim **1**, wherein the weights are calculated based on respective logarithms of at least one of the view counts and the rankings.

4. The method of claim **3**, wherein the respective logarithms of at least one of the view counts and the rankings are quantized before being used to calculate the weights.

5. The method of claim **1**, further comprising:

merging the respective N-grams counts without the weights to obtain merged un-weighted respective N-gram counts; and

calculating a respective probability for each of the N-grams based on the merged un-weighted respective N-gram counts,

wherein a final probability for each of the N-grams is respectively calculated by interpolating, using a predetermined interpolation coefficient, between the respective probability for a corresponding one of the N-grams based on the merged weighted respective N-gram counts and the respective probability for the corresponding one of the N-grams based on the merged un-weighted respective N-gram counts.

6. The method of claim **5**, wherein the respective probability for each of the N-grams based on the merged un-weighted respective N-gram counts is calculated using a maximum likelihood method.

7. The method of claim **5**, wherein the interpolation coefficient is determined based on a transcribed text.

8. The method of claim **1**, wherein at least one of the view counts and the rankings correspond to at least one of titles and section headers.

9. The method of claim **1**, further comprising:

merging the respective N-grams counts without the weights to obtain merged un-weighted respective N-gram counts; and

calculating a respective probability for each of the N-grams based on the merged un-weighted respective N-gram counts,

wherein the N-gram counts to which the weights are applied are 1-gram counts corresponding to 1-grams, the N-gram counts to which the weights are not applied are 2-gram counts or greater corresponding to 2-grams or greater, and wherein the respective probability for each

of the 2-grams or greater is adapted to satisfy the respective probability for at least one of the 1-grams.

10. A method for calculating N-gram probabilities in a language model, comprising:

sorting a plurality of pages or a plurality of documents based on at least one of view counts and rankings to obtain sorted pages or sorted documents;

classifying the sorted pages or the sorted documents into M subsets;

counting N-grams in each of the M-subsets;

estimating respective N-gram probabilities for each of the N-grams in each of the M-subsets using a maximum likelihood method;

interpolating the estimated respective N-gram probabilities to minimize a cross entropy there between; and

decoding an utterance, by a speech recognition system, based on the N-gram probabilities in the language model.

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